

Article

How Digital Orientation Promotes Technology Standard Innovation: The Serial Mediating Role of Organizational Unlearning and Knowledge Re-Orchestration

Hong Jiang, Chen Chen * and Ye Yuan

School of Business and Management, Jilin University, Jilin 130012, China; jiang_hong@jlu.edu.cn (H.J.);
yuanye_jlu@163.com (Y.Y.)

* Correspondence: chenchen_jlu@163.com

Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- This study enriches system practice research by revealing how digital orientation triggers coordinated changes in organizational cognition and knowledge systems to achieve standard innovation outcomes.
- By integrating strategic management theory and resource orchestration theory, this study proposes a progressive transmission logical framework, thereby constructing a systematic and complex model.

What are the main findings and/or the implications of the main findings?

- Organizational unlearning and knowledge re-orchestration play a serial mediating role in the relationship between digital orientation and technology standard innovation; knowledge inertia negatively moderates the relationship between the two mediators.
- The findings offer actionable guidance for enterprises to deploy digital strategy, adjust organizational cognition and optimize knowledge management systems to gain standard competitiveness.

Abstract

Against the backdrop of digital transformation, enterprises take digital orientation as a strategic foundation and compete for standard-setting authority to gain core competitive advantages. Although prior research indicates that digital orientation positively influences innovation, research on how digital orientation affects technology standard innovation remains limited. Technology standard innovation under digital practices is more complex and knowledge-intensive than that in the traditional industrial era. The mechanism by which digital orientation drives technology standard innovation requires more attention. Drawing upon strategic management theory and resource orchestration theory, this study proposes a serial mediation model to reveal how digital orientation influences technology standard innovation. We collected survey data from 480 Chinese enterprises via questionnaires and tested the model using partial least squares structural equation modeling. The results indicated that digital orientation has a significant positive impact on technology standard innovation; organizational unlearning and knowledge re-orchestration play a serial mediating role in this relationship; and knowledge inertia negatively moderates the relationship between organizational unlearning and knowledge re-orchestration. This study offers insights for traditional enterprises establishing efficient organizational change and knowledge management mechanisms to gain standard influence and innovation benefits.



Academic Editor: Mitsuru Kodama

Received: 13 June 2026

Revised: 6 August 2026

Accepted: 12 August 2026

Published: 21 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: digital orientation; technology standard innovation; organizational unlearning; knowledge re-orchestration; knowledge inertia

1. Introduction

Digital transformation drives enterprises to alter traditional operational management models, achieve significant business improvements, form new value creation models, and enhance core competitiveness [1,2]. Most digital transformation research focuses on value creation, including significant strategic shifts in processes, services, and products [3]. However, the impact that digitalization brings to technology standards remains underexplored. Standards serve as the underlying logic for digital technology operation [4] and become the key battleground for core competitiveness in the digital economy [5]. The widespread adoption of information technology necessitates global compatibility among systems, products, and services, with technology standards serving as the critical enabler [6,7]. As digital technologies advance, technology standards grow increasingly vital by fostering interoperability [8,9]. Currently, globalized manufacturing and digital transformation pose new challenges to the form, content, and application of standards [10]. Enterprises need to improve their technology standards to adapt to digital advancements. Specifically, technology standard innovation (TSI) requires enterprises to fully leverage digital technologies, adopt new processes and architectures, and explore novel standard forms. The digital transformation of traditional enterprises necessitates top-down coordination and deployment at the strategic level. It involves strategically prioritizing the full utilization of changes and opportunities brought by digital technologies, along with their societal impacts. Therefore, introducing digital orientation (DO) into TSI is a prerequisite for the digital transformation of standards.

DO evolves from strategic orientation in a digital context, describing a strategic positioning of enterprises in applying digital technologies [11]. The existing literature has confirmed the positive impact of DO on innovation, especially in the fields of knowledge management and information management. DO not only enables enterprises to establish new partnerships to access wider knowledge sources, but also optimizes internal processes to enhance innovation performance [12,13]. At the same time, DO is characterized by utilizing digital technologies, enabling enterprises to connect digital data access links and coordinate digital systems to improve financial performance [14]. However, the impact of DO on TSI has been insufficiently examined. First, differing from general innovation, TSI can generate significant network effects. Once a standard is widely adopted, it forms a large user base [15], and its market influence far exceeds that of ordinary product innovation. Second, TSI involves greater knowledge complexity, requiring the integration of knowledge from different fields [16] to form a complex knowledge system. It differs from a one-dimensional technological innovation. Finally, the development cycle for technology standards is lengthy [17], so TSI requires greater resource investment. This driving mechanism differs significantly from those of general innovation models. Therefore, it is essential to explore how DO influences TSI.

As a strategic antecedent, the process by which DO influences TSI is relatively complex, and its intermediate transmission mechanisms remain to be revealed. This transmission process is rooted in the analytical perspective of strategic management theory. Strategy implementation is first reflected in the transformation of organizational cognitive and behavioral patterns. Existing research on digital transformation focuses more on the incremental innovation path of new knowledge acquisition and generation [18], ignoring the pre-requisite role of breaking old paths. During the digital transformation process, enterprises are prone to being hindered by inherent paths and concepts, as well as routines [19].

Organizational unlearning (OU) can promote the update of organizational concepts and routines and create space for the introduction of new knowledge and technologies [20]. OU is the key for enterprises to adapt to digital development, providing a cognitive basis for subsequent TSI activities.

Strategic implementation also depends on how enterprises coordinate and allocate their resources. Digital technology has reshaped the knowledge management process [21]; thus, the advantage of knowledge re-orchestration (KRO) has become increasingly prominent. TSI's core output is essentially the condensation of multi-dimensional knowledge. If only relying on a single step among knowledge acquisition, absorption, integration and utilization, the entire process of technology standard formulation and innovation cannot be supported. Systematic KRO requires completing the deconstruction, screening, integration and reconfiguration of knowledge. This is in line with the viewpoints of resource orchestration theory, where the competitive advantage of enterprises stems from the effective integration and utilization of resources [22].

Furthermore, OU establishes the cognitive foundation and unlocks knowledge space for KRO. Inherent knowledge routines and outdated cognitive frameworks induce organizational inertia [23,24]. This confines enterprises to conventional knowledge combinations and hinders the formation of digitally driven knowledge architectures. OU enables enterprises to abandon obsolete technological paradigms, break rigid knowledge boundaries, and release space occupied by outdated expertise [25]. Enterprises can update knowledge and conduct effective KRO after overcoming path dependence derived from prior knowledge stocks [26]. It is worth noting that the transformation from OU to KRO depends on the organization's internal knowledge processing patterns and is context-dependent. The key question of "under what conditions can OU be effectively transformed into KRO" requires further exploration. Research indicates that knowledge inertia (KI) is an important boundary factor restricting the efficiency of organizational innovation [27]. The essence of KI lies in enterprises' path dependence on existing knowledge and experiences [28], which aligns closely with the transformation context from OU to KRO. Even if enterprises break old cognitive frameworks through OU, high KI will lead them to fall back on familiar knowledge paths, thus weakening the efficiency of KRO. Accordingly, this study introduces KI as a moderating variable to explore its boundary role in the relationship between OU and KRO.

Although scholars have recognized DO's impact on innovation, there are still three key gaps in the field of standardization. First, existing research primarily links DO to traditional product innovation and process innovation [12,29], and rarely touches upon the field of TSI. Although the direct relationship between DO and TSI stems from research conclusions on the impact of DO on general innovation, it may not be fully applicable to the TSI context. Therefore, the impact of DO on TSI requires targeted examination. Second, there is a lack of organizational-level intermediary support to explain how DO is transformed into complex and knowledge-intensive TSI outcomes. On the one hand, TSI exhibits path-dependence characteristics that go beyond those of general innovation, and OU will play a key role in transforming DO into practical TSI outcomes. On the other hand, KRO has been demonstrated to be the core mechanism through which knowledge resources are transformed into innovation outputs. KRO also effectively explains the systematic integration of multi-dimensional, cross-disciplinary knowledge required to achieve TSI. More importantly, existing research often discusses OU and KRO separately as a single mediating mechanism [30,31], ignoring the sequential logical relationship between them. Studying the serial mediation of OU and KRO as a link between strategy and innovation is very valuable. Third, considering that technology standards themselves have characteristics such as high knowledge complexity [32], improving technology standards places higher demands on knowledge. The process of transforming OU into KRO is more likely to be

hindered by the original knowledge system. Especially in the digital economy era, the speed of knowledge iteration has grown exponentially, and the inhibitory effect of KI on KRO implementation will be further amplified, revealing the specific characteristics and role of KI to better understand the dilemmas in the process of OU transforming into KRO.

To address the above research gaps, this study constructs a moderated serial mediation model: First, we examine the direct relationship between DO and TSI. Second, we examine OU's mediating role and KRO's mediating role in the relationship between DO and TSI. Third, we introduce OU and KRO as serial mediators to reveal the transmission mechanisms between DO and TSI. Finally, we investigate KI's moderating role in the relationship between OU and KRO. This study offers four contributions. First, it proposes a progressive transmission logical framework and enriches the integration of research on strategic management theory and resource orchestration theory. Second, it empirically verifies the impact of DO on TSI and advances the study of TSI during digital transformation. Third, it reveals the serial mediating role of OU and KRO in the relationship between DO and TSI, expanding the research scope of OU and KRO. Finally, it explores the boundary condition under which OU affects KRO, thereby enriching the micro-mechanisms of KI.

2. Theory and Hypotheses

The theoretical foundation of this study rests on two interrelated paradigms: strategic management theory and resource orchestration theory. These two theories jointly provide a comprehensive and phased explanation for the entire transmission chain from strategic guidance to innovation output. Within strategic management theory, an organization's strategic orientation is regarded as the strategic direction of correct behaviors adopted to achieve sustained superior performance [33]. Previous research indicates that standards have long been central to enterprise market competition [34]. Particularly for enterprises undergoing digital transformation, the process of promoting standards into the market and achieving their adoption constitutes the path to performance attainment. The role of DO manifests more prominently at the strategic leadership level [35], guiding enterprises to leverage digital technologies for adjusting and innovating production and operational activities, while also facilitating TSI.

According to strategic management theory, strategic orientation determines organizational behavior, which, in turn, affects organizational performance. Digital transformation can be broadly understood as the process of leveraging digital technologies to drive strategic organizational change [1,36]. Traditional enterprises often exhibit deep-rooted operational philosophies, management systems, knowledge structures, and product development approaches formed over decades of development, leading to organizational inertia [37,38], which conflicts with the demands and developmental philosophy of digital transformation. Purposeful OU enables enterprises to focus on capabilities conducive to organizational change, thereby driving organizational transformation and technological innovation. DO, as a top-level strategic positioning, has a relatively weak direct impact on innovation activities. It must first be transformed into cognitive and behavioral changes at the organizational level. OU is precisely the core behavior during the implementation of DO, where the organization breaks away from its old cognitive framework and discards outdated conventions, laying the foundation for subsequent TSI activities.

According to resource orchestration theory, an enterprise's possession of resources is not the direct cause of its competitive advantage, which lies, rather, in how resources are dynamically managed and utilized [39]. After completing OU at the cognitive level, enterprises can utilize digital technology to re-arrange their internal and external knowledge resources, and then apply these re-organized knowledge resources to TSI activities. Enterprises need to possess the capability to comprehensively integrate their traditional

and digital resources, breaking path dependencies on existing organizational, production, and service models to achieve innovation [37]. Therefore, leveraging the characteristics of digital technologies, we introduce KRO as another mediating mechanism. Enterprises' use of digital technologies to construct, integrate, and utilize internal and external knowledge also facilitates TSI. Furthermore, both OU and KRO involve the processing of knowledge resources. The process of converting OU into KRO is context-dependent and is more susceptible to constraints imposed by KI.

In sum, strategy orientation provides enterprises with a pathway to develop technology and enhance innovation [40]. The strategy first guides the transformation of an enterprise's cognitive and behavioral patterns, which is then ultimately translated into innovation performance through coordinating and allocating resources. The impact of DO on TSI follows a progressive transmission pathway: "strategic guidance–cognitive transformation–resource orchestration–innovation output". Accordingly, this study proposes a serial mediating path: DO first promotes OU, then drives the process of KRO, and finally promotes TSI. This logic is consistent with the actual process of implementing enterprise digitalization strategies and can accurately reveal the micro-mechanism by which DO affects TSI. In addition, this study takes into account the moderating effect of KI and develops a comprehensive research framework.

2.1. Technology Standard Innovation

Standardization is recognized as an innovative activity [5]. TSI refers to enterprises undertaking innovative approaches within the standardization process, including standard development, adoption, implementation, and promotion across various activities such as research and development, production, and services. It encompasses creating entirely new technology standards, revising or enhancing existing standards, and benchmarking against other technology standards [41,42]. Those that have successfully innovated technology standards will be able to develop new products, establish technical barriers, and even formulate competition rules to maintain a more lasting competitive advantage in the market [43].

2.2. Digital Orientation and Technology Standard Innovation

As digital technologies increasingly gain recognition as vital tools for innovation, DO demonstrably influences diverse innovation activities within enterprises, including TSI. On the one hand, DO represents an enterprise's commitment to leveraging digital technologies to produce new products or deliver new services [11], thereby laying the strategic foundation and providing directional guidance for TSI. Digital technologies typically form complex systems comprising hardware and software components, requiring development by different suppliers in diverse ways. Existing enterprise technology standards are often incompatible with digital technologies and tend to prove inadequate during digital technology application, forcing enterprises to revise them or develop new ones. This necessitates that enterprises adopt measures, namely TSI, to ensure system interoperability [6]. Subsequently, the widespread adoption of digital technologies necessitates ensuring compatibility among systems, products, and services in the marketplace, further driving enterprise innovation in technology standards [7].

On the other hand, DO can provide digital technology support and implementation pathways for TSI. First, DO drives the intelligent and data-driven upgrade of standard forms. With the advancement of DO, the application of digital technologies is becoming gradually deepened, changing the form and carrier of technology standards. This not only makes standards easier to store, retrieve, and share, but also enhances the reliability of standard testing, certification, and validation processes. For example, many organizations are currently promoting SMART (Standards Machine Applicable Readable, and Transferable)

standards to advance the digitalization of standards [44]. Second, DO leverages advanced digital tools to improve the efficiency and quality of standards development. The adoption of advanced digital tools, such as cloud platforms and big data analytics, expands the scope of relevant information searches and enhances processing efficiency [45]. This helps break down information barriers in traditional standards development, better align with market information, and improve the efficiency and quality of standards development. Third, DO is also regarded as a resource that can provide enterprises with sustained competitive advantage [46,47]. DO can help enterprises establish new connections with more partners, access broader sources of knowledge or relational resources, and apply them to TSI activities [12]. Therefore, we propose the following hypothesis:

H1. *DO positively influences TSI.*

2.3. *The Mediating Role of Organizational Unlearning*

From the strategic perspective, OU is the process by which organizations proactively discard outdated or obsolete knowledge, routines, and beliefs to create space for learning new things [48,49]. The advent of the digital age challenges traditional enterprises' cognitive patterns, rendering their cultural mindset unsuitable for digital practices. In this context, OU becomes pivotal for integrating digital technologies with traditional operations. Outdated enterprise mindsets can hinder the adoption of new technologies [50], as digital technologies may conflict with existing technical systems. To achieve digital transformation goals, traditional enterprises adopt various digital technologies, overcome current organizational inertia, and engage in OU to enhance adaptability and renewal capabilities.

Rapidly advancing digital technologies accelerate the renewal and iteration of products and services in the market, rendering market knowledge obsolete quickly [30]. Research indicates that OU serves as a catalyst for absorbing new and more suitable information, learning, organizational change, and innovation [51]. OU facilitates resource acquisition and utilization [20], enabling enterprises to secure the resources required for developing new technology standards. Without OU, enterprises struggle to acquire new knowledge and establish new routines, as entrenched routines may create capability traps and cognitive deadlocks that impede external knowledge acquisition [52]. Thus, OU plays a positive role in TSI.

Overall, the DO of an enterprise charts the strategic course for its digital transformation, clarifying its commitment to leveraging digital technologies. By introducing new digital technologies, enterprises abandon certain legacy technologies and routines, thereby facilitating the absorption of new resources required for TSI and creating space for their innovation activities. Therefore, we propose the following hypothesis:

H2. *OU mediates the relationship between DO and TSI.*

2.4. *The Mediating Role of Knowledge Re-Orchestration*

Resource orchestration theory posits that effective resource management constitutes the true source of competitive advantage, emphasizing the structuring, bundling, and utilization of resources [22]. Grant (1996) contended that knowledge represents the most critical strategic resource for enterprise development [53]. Particularly within digital practices, the value of knowledge resources is continuously unearthed [54]. Based on this, the concept of KRO was proposed and defined as the comprehensive process by which enterprises utilize digital technologies to construct, bundle, and coordinate internal and external knowledge [31]. Supported by digital infrastructure, enterprises are reexamining, reorganizing, and deploying their internal and external knowledge resources using new approaches that differ from traditional knowledge orchestration.

On the one hand, highly digitally oriented enterprises perceive, acquire, filter, and process digital information more extensively, which is also a process that involves knowledge acquisition and utilization, thereby facilitating enterprises' KRO. By introducing and applying new digital technologies and tools, enterprises can transcend organizational boundaries to identify and access knowledge from external stakeholders and competitors [55], gaining insights into customer market demands. Simultaneously, leveraging digital systems or platforms enables enterprises to process and store vast amounts of data more efficiently, enhance the flow of internal and external knowledge, and integrate and update internal knowledge repositories [56,57]. DO facilitates KRO by expanding knowledge acquisition channels, reducing integration and allocation costs, and optimizing existing knowledge to form new combinations.

On the other hand, KRO promotes the construction, bundling, and coordination of knowledge resources, thereby advancing TSI. TSI inherently involves knowledge recombination [58]. TSI demands highly complex knowledge [59], requiring enterprises to accumulate and master knowledge resources that are difficult to imitate. For instance, the standardization and innovation of broadband mobile services are driven by the need to integrate complex and diverse technical knowledge [60]. Due to the social complexity and non-imitable nature of knowledge, externally acquired knowledge is often fragmented and fails to meet the systematic knowledge requirements for standard-setting, which necessitates KRO. This process enables enterprises to continuously accumulate advanced knowledge, form knowledge combinations tailored to market demands, and establish high-quality technology standards [61].

In summary, the use of digital technologies facilitates the KRO process within enterprises, enabling them to achieve a standardized development trajectory for technologies and accumulate standardized knowledge. This promotes the integration and utilization of high-quality complex knowledge, thereby forming new knowledge combinations and providing an effective pathway for TSI. Therefore, we propose the following hypothesis:

H3. *KRO mediates the relationship between DO and TSI.*

2.5. The Serial Mediating Role of Organizational Unlearning and Knowledge Re-Orchestration

OU creates favorable conditions for knowledge acquisition, accumulation, and the generation of new knowledge by discarding knowledge and routines no longer needed by an enterprise [62]. Abandoning existing outdated knowledge and behaviors makes the enterprise's learning and transformation processes more efficient [63]. OU not only saves management costs associated with redundant resources but also frees up more space for subsequent standardized knowledge acquisition and accumulation. Particularly when an enterprise's existing standardized knowledge system is incompatible with external knowledge, subsequent knowledge activities face significant obstacles. OU can transform enterprise beliefs and routines, increasing the likelihood of integrating new and old knowledge [64,65]. Research also indicates that new knowledge generation is indispensable following OU, as enterprises must establish new beliefs and routines to maintain normal operations [66]. Thus, OU demonstrably facilitates KRO.

According to strategic management theory, DO is a strategy whereby enterprises apply digital technologies to achieve digital transformation [11]. Effective strategy implementation relies on resource coordination and allocation. As digital technologies are adopted, internal conflicts between old and new beliefs inevitably arise, where OU plays a crucial role. Especially for traditional enterprises, past successful experiences are often codified as useful knowledge and crystallized into organizational beliefs and routines [67], guiding future innovation activities. Digital transformation necessitates reshaping and reconstructing enterprises' traditional cognition, routines, and structures [68]. By integrating resource

orchestration theory, enterprises discard outdated knowledge hindering development and leverage digital technologies to acquire necessary external knowledge [69]. By integrating and utilizing internal and external knowledge, they transform it into new knowledge systems, driving TSI. Particularly in processing non-codified knowledge during standardization, KRO serves to accumulate existing knowledge and construct new knowledge. Therefore, we propose the following hypothesis:

H4. *OU and KRO have a serial mediating effect in the relationship between DO and TSI.*

2.6. The Moderating Role of Knowledge Inertia

KI negatively moderates the relationship between OU and KRO. KI primarily refers to the tendency of individuals or organizations to follow routine procedures during knowledge activities, relying on stable knowledge sources and accumulated experiences [28]. Enterprises with high KI tend to repeatedly address problems using existing knowledge and experience. This path dependence is prominently reflected in the transformation from OU to KRO. OU requires enterprises to discard outdated and useless knowledge [70], thereby creating the necessary knowledge space for the introduction of new knowledge and KRO. During proactive knowledge acquisition, construction, bundling, and coordination, enterprises with high KI often face constraints from existing routines [71], generating resistance to learning and applying new knowledge, which hinders KRO. High KI leads enterprises to prioritize reinforcing existing knowledge combinations over expanding new knowledge [72]. This weakens their willingness to explore, acquire, and integrate cutting-edge digital resources, making it difficult for them to break through the boundaries of their original knowledge architecture to update and integrate new knowledge [73]. On the contrary, enterprises with low KI can flexibly absorb new digital knowledge [27], integrate knowledge resources both internally and externally across boundaries, and efficiently restructure their knowledge systems. Therefore, we propose the following hypothesis:

H5. *KI negatively moderates the positive relationship between OU and KRO.*

The conceptual framework established in this study is seen in Figure 1.

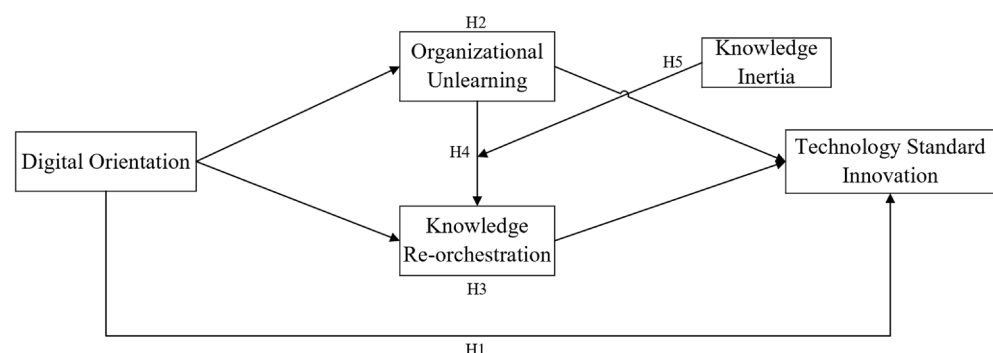


Figure 1. Theoretical framework of this study.

3. Research Methodology

3.1. Sample and Data Collection

This study focuses on enterprises undergoing digital transformation. The research questionnaire addresses enterprises' DO and TSI, necessitating respondents with specialized expertise and a high level of enterprise awareness. Consequently, managers familiar with the enterprise's development status, strategic planning, and standardization practices were selected as respondents. The scales, primarily originating from research in the En-

glish language, were translated using the back-translation method. Two English-proficient experts in the field were invited to participate in this process to minimize interpretation discrepancies during Chinese–English translation. They meticulously reviewed each item’s phrasing and specialized terminology definitions, making appropriate additions where necessary. The translated draft was then shared with other doctoral candidates within the research team and additional experts in the field for feedback and further refinement, ensuring the questionnaire design’s normalization and validity.

We collected research data by distributing online surveys via the Credamo platform. Credamo is a professional academic survey platform with a verified pool of enterprise respondents and rigorous data quality controls. To reduce common method bias, we implemented procedural controls during data collection: we informed respondents that the survey was anonymous; the data would be used solely for academic research; and there were no right answers, in order to reduce social desirability bias. The data were collected from November 2024 to February 2025. The survey samples are distributed across multiple provinces covering the eastern, central, and western regions of China. Rigorous data cleaning procedures were conducted prior to formal analysis. Invalid questionnaires were excluded based on three predefined objective criteria: linear responses where all items were answered identically; incomplete questionnaires; and missing values in core construct items. In total, 480 valid responses with complete data were obtained, yielding a valid response rate of 76.19%.

3.2. Measures

The scales used in this study primarily draw upon established measures adopted in existing research, with appropriate adjustments made to align with the specific research content. All variables are measured using a Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

Digital orientation (DO): DO refers to an enterprise’s deliberate strategic positioning to capitalize on opportunities presented by emerging digital technologies. Drawing from Quinton et al. (2018) [74] and Arias-Pérez et al. (2022) [75], it is measured using seven items, including “Our enterprise has developed a clear vision regarding how new digital technologies contribute to business value.”

Organizational unlearning (OU): OU refers to an enterprise’s process of altering or discarding outdated routines, beliefs, and knowledge to make space for new elements. Drawing on Lyu et al. (2020) [30], it is measured using six items, including “Our enterprise is ready to acquire new technologies and knowledge from various channels.”

Knowledge re-orchestration (KRO): KRO is the comprehensive process by which enterprises actively manage internal and external knowledge using digital technologies. Drawing on Tang et al. (2023) [31], it is measured using four items, including “Our enterprise will actively interact with various knowledge subjects (e.g., customers, consumers, partners, suppliers) using digital technologies to stimulate the generation of new knowledge.”

Technology standard innovation (TSI): TSI refers to innovation in the processes of establishing, adopting, implementing, and promoting standards across R&D, production, services, and other activities. Drawing from Jiang et al. (2022) [42], it is measured using five items, including “Our enterprise can issue new technology standards or compete with other standards in a relatively short time.”

Knowledge inertia (KI): KI refers to the degree to which an enterprise relies on existing knowledge resources and past experiences in its knowledge management processes. Drawing on Yu et al. (2020) [72], it is measured using five items, including “Our enterprise uses past knowledge and experience to solve new problems.”

Control variables: We selected enterprise age, enterprise size, ownership nature, and industry as control variables based on prior standardization research [76]. First, older enterprises typically have more extensive experience with standardization but also exhibit greater organizational inertia, which may affect TSI. Second, larger enterprises have more resources and influence, enabling them to participate more actively in TSI activities. Third, state-owned enterprises face greater institutional pressure and are more likely to participate in government-led standard-setting projects. Finally, the pace of technological iteration varies across different industries, which may affect the frequency of TSI activities. We have classified industries into five major categories. For example, the manufacturing industry covers the automotive, electronics, pharmaceutical and food industries, as well as general-purpose and specialized equipment, among others. The basic characteristics of the sampled enterprises are distributed as shown in Table 1.

Table 1. Basic characteristics of the sampled enterprises.

Characteristic	Classification	Number	Proportion (%)
Enterprise age	1–4 years	15	3.13
	5–10 years	109	22.71
	11–20 years	209	43.54
	>20 years	147	30.63
Enterprise size	1–50 people	19	3.96
	51–200 people	125	26.04
	201–1000 people	210	43.75
	>1000 people	126	26.25
Nature	State-owned enterprises	99	20.63
	Private enterprises	356	74.17
	Foreign-funded or joint venture enterprises	25	5.21
Industry	Manufacturing	223	46.46
	Information transmission, computer, and software	139	28.96
	Wholesale and retail	23	4.79
	Service	43	8.96
	Other	52	10.83
Total		480	100

3.3. Analytical Strategy

This study adopted a partial least squares structural equation model (PLS-SEM) for estimation. The reasons are as follows: First, it is suitable for complex models with multiple mediating and moderating effects and has advantages in handling interaction effects among latent variables. Second, the survey data exhibited slight deviations from normality (skewness < |2|, kurtosis < |7|). PLS-SEM has more lenient requirements regarding data distribution compared to covariance-based structural equation modeling (CB-SEM).

Prior to formal modeling, this study used the Mahalanobis distance to test for outliers. We included all observed items in the calculations and used a p -value of <0.001 as the criterion for identifying multivariate outliers. A total of 13 potential multivariate outliers were identified. A comparison of the path coefficients and significance results in the PLS-SEM model before and after the removal of outliers revealed no significant changes in the core research conclusions. To avoid bias resulting from subjective data exclusion, this study retained all valid samples for subsequent analysis.

In addition, we conducted a prior statistical power analysis using G*Power 3.1 [77]. We adopted $\alpha = 0.05$, power = 0.95, and a conservative medium effect size ($f^2 = 0.15$) for the model's most complex regression with eight predictors. The analysis showed a minimum

required sample size of 160, indicating that our sample of 480 enterprises provides more than sufficient statistical power to capture the hypothesized effects.

4. Results

4.1. Common Method Bias

A single-factor confirmatory factor analysis was conducted to test all items for common method bias. The results indicated that the revised model ($\chi^2/\text{df} = 11.088$, $\text{NFI} = 0.599$, $\text{RFI} = 0.566$, $\text{CFI} = 0.621$, and $\text{RMSEA} = 0.145$) was significantly worse than the original model ($\chi^2/\text{df} = 1.997$, $\text{NFI} = 0.930$, $\text{RFI} = 0.922$, $\text{CFI} = 0.964$, and $\text{RMSEA} = 0.046$), indicating no severe common method bias issues. We further conducted Harman's single-factor test: the first factor accounted for 41.82% of the total variance, which is below the 50% threshold [78]. At the same time, the eigenvalues of the five factors exceeded 1.0, and they collectively accounted for 70.42% of the total variance. These results indicated that there was no significant common method bias. In addition, the Variance Inflation Factor (VIF) values of all variables fell below the recommended threshold of 5, indicating no severe multicollinearity issues.

4.2. Reliability and Validity Analysis

As shown in Table 2, all variables demonstrated Cronbach's alpha and composite reliability coefficients exceeding 0.7, indicating high reliability levels. All item loadings exceeded 0.7, and AVE values exceeded 0.5, indicating strong convergent validity for the measurement model. The square roots of AVE for latent variables exceeded their respective correlations with other variables, and HTMT values remained below 0.85 (see Table 3), indicating good discriminant validity for the measurement model.

Table 2. Results of reliability and convergent validity.

Variables	Items	Loadings	Cronbach's α	CR	AVE
DO	DO1	0.861	0.931	0.944	0.707
	DO2	0.836			
	DO3	0.838			
	DO4	0.850			
	DO5	0.834			
	DO6	0.841			
	DO7	0.825			
OU	OU1	0.765	0.886	0.914	0.638
	OU2	0.784			
	OU3	0.833			
	OU4	0.785			
	OU5	0.835			
	OU6	0.789			
KRO	KRO1	0.854	0.860	0.905	0.705
	KRO2	0.787			
	KRO3	0.856			
	KRO4	0.860			
TSI	TSI1	0.814	0.874	0.909	0.666
	TSI2	0.807			
	TSI3	0.841			
	TSI4	0.800			
	TSI5	0.816			
KI	KI1	0.865	0.926	0.944	0.772
	KI2	0.882			
	KI3	0.872			
	KI4	0.883			
	KI5	0.891			

Table 3. Results of discriminant validity.

	DO	OU	KRO	TSI	KI
Fornell–Larcker					
DO	0.841				
OU	0.594	0.799			
KRO	0.675	0.642	0.840		
TSI	0.565	0.537	0.571	0.816	
KI	0.308	0.321	0.359	0.323	0.879
HTMT Ratio					
DO					
OU	0.652				
KRO	0.751	0.735			
TSI	0.624	0.604	0.658		
KI	0.329	0.352	0.397	0.359	

4.3. Model Assessment

Before analyzing the results of the hypotheses, we evaluated the structural model. The results are shown in Table 4. First, the SRMR value was 0.052 (<0.08) and the NFI value was 0.895 (close to the recommended value of 0.9), indicating that the model fit the data well. Second, R^2 represents the proportion of the dependent variable explained by the model. The R^2 values were 0.353 for OU, 0.572 for KRO, and 0.437 for TSI. These results indicate that the model in this study explains 35.3% of the variance in OU, 57.2% of the variance in KRO, and 43.7% of the variance in TSI. Furthermore, the Q^2 values for OU, KRO, and TSI were all greater than 0, indicating that the model possesses sufficient predictive power. Finally, f^2 was used to assess the relative strength of the influence of exogenous variables on endogenous variables. The f^2 value for the effect of DO on OU was 0.544, which is classified as a large effect; the f^2 value for the effect of DO on KRO was 0.199, which is classified as a medium effect; the f^2 value for the effect of DO on TSI was 0.078, classified as a small effect; the f^2 value for the effect of OU on KRO was 0.114, classified as a small effect; the f^2 value for the effect of OU on TSI was 0.038, classified as a small effect; and the f^2 value for the effect of KRO on TSI was 0.042, classified as a small effect. Overall, the f^2 values for the effects between variables were all greater than 0.02, indicating that the model effectively captures the relationships among the variables.

Table 4. Results of explanatory power and predictive ability.

Variables	R^2	Adjusted R^2	Q^2 Predict
OU	0.353	0.351	0.346
KRO	0.572	0.569	0.497
TSI	0.437	0.429	0.352

4.4. Results Analysis

This study constructed multiple SEMs to sequentially examine main effects, mediating effects, and moderating effects. The path relationship estimation results were obtained using the SmartPLS 4 software with 5000 bootstrapping samples.

Model 1 tested the main effect of the independent variable DO on the dependent variable TSI, with control variables included. The results indicate (see Table 5) that DO has a significant positive impact on TSI ($\beta = 0.589$, $p < 0.001$), and H1 is supported.

Table 5. Results of the structural equation model.

Model	Path	Coefficient	Standard Error	t-Value	p-Value	LLCI	ULCI	Results
Model 1: Main effect								
	DO → TSI	0.589	0.049	12.075	0.000	0.492	0.680	Supported
Model 2: Mediating effect								
	DO → TSI	0.308	0.068	4.553	0.000	0.167	0.432	Supported
	DO → OU	0.594	0.051	11.592	0.000	0.489	0.688	Supported
	DO → KRO	0.454	0.061	7.410	0.000	0.336	0.574	Supported
	OU → KRO	0.372	0.064	5.846	0.000	0.248	0.495	Supported
	OU → TSI	0.201	0.064	3.163	0.002	0.083	0.330	Supported
	KRO → TSI	0.229	0.067	3.410	0.001	0.098	0.364	Supported
Model 3: Moderating effect								
	DO → TSI	0.308	0.068	4.551	0.000	0.167	0.432	Supported
	DO → OU	0.594	0.051	11.592	0.000	0.489	0.688	Supported
	DO → KRO	0.384	0.066	5.860	0.000	0.259	0.516	Supported
	OU → KRO	0.294	0.295	4.213	0.000	0.160	0.434	Supported
	OU → TSI	0.201	0.064	3.162	0.002	0.083	0.329	Supported
	KRO → TSI	0.229	0.067	3.410	0.001	0.098	0.364	Supported
	KI × OU → KRO	−0.136	0.053	2.585	0.010	−0.236	−0.028	Supported

Model 2 added the mediating variables OU and KRO into Model 1. The results indicate that DO has a significant positive impact on OU ($\beta = 0.594, p < 0.001$) and KRO ($\beta = 0.454, p < 0.001$). OU ($\beta = 0.201, p < 0.01$) and KRO ($\beta = 0.229, p < 0.01$) have a significant positive impact on TSI, providing preliminary support for H2 and H3. Further, OU has a significant positive impact on KRO ($\beta = 0.372, p < 0.001$), offering preliminary evidence for H4. The mediation effect test was then conducted, and the results are shown in Table 6. The mediating effect of OU in the relationship between DO and TSI is significant ($\beta = 0.119, p < 0.01$), and the mediating effect of KRO in the relationship between DO and TSI is also significant ($\beta = 0.104, p < 0.01$), supporting H2 and H3. The serial mediating effect of OU and KRO in the relationship between DO and TSI is significant ($\beta = 0.051, p < 0.01$), supporting H4.

Table 6. Results of the mediating effect.

Effect	Path	Coefficient	Standard Error	t-Value	p-Value	Results
Total effect	DO → TSI	0.581	0.050	11.698	0.000	Supported
Direct effect	DO → TSI	0.308	0.068	4.553	0.000	Supported
Indirect effect	DO → OU → TSI	0.119	0.041	2.917	0.004	Supported
	DO → KRO → TSI	0.104	0.037	2.834	0.005	Supported
Serial mediation effect	DO → OU → KRO → TSI	0.051	0.017	3.043	0.002	Supported

Model 3 included the moderator variable KI and its interaction term with the variable OU, building upon Model 2. As shown in Table 5, the results indicate that OU has a significant positive impact on KRO ($\beta = 0.294, p < 0.001$). KI negatively moderates the positive relationship between OU and KRO ($\beta = -0.136, p < 0.05$), supporting H5.

4.5. Robustness Tests

To ensure the robustness of the analysis results, we conducted three robustness tests. First, we removed two control variables for testing: enterprise age and enterprise size. Second, we randomly sampled 70% of the original sample for retesting. Finally, we replaced the scale of DO with the one used in Kindermann et al. (2024) [79] and repeated the analysis. The results from these tests were consistent with the original findings, and the results are, thus, robust.

5. Discussion

This study examined how DO influences TSI and the roles of OU, KRO, and KI in this process. This study contributes to the integrated field of digitalization and standardization. The results provide several points worthy of further explanation and discussion.

The serial mediation model can be linked to broader theoretical perspectives. From the dynamic capability perspective, OU corresponds to sensing capability to identify and discard outdated routines, while KRO corresponds to reconfiguring capability to reorganize resources using digital technologies [80]. The $DO \rightarrow OU \rightarrow KRO \rightarrow TSI$ pathway essentially reflects the process by which enterprises transform DO into dynamic capabilities and ultimately gain competitive advantage through TSI. Compared to the broad perspective of dynamic capabilities, our model provides a more specific and actionable micro-level explanation of the mechanisms through which DO is transformed into TSI. Furthermore, the “OU–KRO” sequence complements absorption capacity theory. This theory has traditionally emphasized the acquisition of new knowledge [81] but has paid less attention to the prerequisite of discarding old knowledge.

Our findings should be interpreted within specific boundary conditions. Contrary to the generally positive view of digital transformation, some studies suggest that once digital transformation reaches a certain level, it may have negative effects [82]. Excessive digitalization can also hinder an organization’s ability to make real-time adjustments to innovation due to organizational inertia, thereby suppressing its innovation performance [83]. Furthermore, in certain specific contexts, digital investments may lead to technological lock-in and path dependence [19], which, in turn, reinforce organizational inertia. For enterprises with highly rigid institutional structures, poor adaptation to digital tools may solidify existing power structures and outdated routines [84], thereby weakening the positive relationship between DO and OU. Enterprises that have long maintained government ties have become increasingly reliant on existing channels of resource acquisition due to power imbalance, thereby increasing organizational inertia [85]. Dysfunctional competition distorts the flow of information and obstructs timely, credible information acquisition [86]. When enterprises face this kind of competition, it prevents managers from abandoning entrenched beliefs, which reduces their OU behavior [87]. This suggests that the impact of DO on OU may not be universally applicable, and future research should further explore its boundary conditions.

Two path effect sizes in these results are relatively small, and the corresponding conclusions require further exploration. The effect size for the moderating effect of KI is -0.136 . Although this value is relatively small, it still holds significant practical implications: given that TSI requires substantial resource investment [88], even a slight decline in the conversion efficiency from OU to KRO could result in a significant loss of TSI output. For enterprises undertaking large-scale digital standards projects, managing KI to improve conversion efficiency can yield significant practical benefits. In addition, the serial mediation effect is relatively low ($\beta = 0.051$), which may be attributed to the following two reasons: First, the transmission pathway is relatively long, and the mediation effect naturally weakens during a multi-step mediation process; second, as mentioned earlier, OU may face significant resistance during the digital transformation process. The practical process of DO being transformed into TSI through this serial mediation may not be as ideal as the theory suggests. Therefore, the serial mediation effect identified in this study should be regarded as preliminary evidence. Future research will need to employ more comprehensive longitudinal study designs to verify its stability and effect strength.

5.1. Theoretical Implications

This study makes several theoretical contributions to the digital innovation and standardization field. The primary and novel theoretical contribution of this study lies in the following. By combining strategic management theory and resource orchestration theory, we propose a logical framework of “strategic guidance–cognitive transformation–resource orchestration–innovation output”. This enriches the integration of research on strategic management theory and resource orchestration theory. This study also provides three other significant contributions.

First, this study empirically verifies the impact of DO on TSI and advances research linking digitization and standardization. Previous studies have demonstrated that DO positively affects various types of innovation within enterprises [12,89]. This positive relationship, though a well-established conclusion from general digital innovation studies, is not fully replicable in the TSI context. TSI’s unique characteristics may both attenuate and exacerbate its impact. Some scholars have begun exploring the connection between digitalization and standardization [90]. However, most previous studies have regarded standardization as an incidental outcome of digital transformation [91] rather than a conscious innovation activity. Based on this, this study extends the influence of DO to the technology standard field. This addresses the research gap caused by the insufficient attention paid to standards innovation in previous studies on digital strategy.

Second, this study reveals the process mechanisms by which DO is transformed into TSI through OU and KRO, and provides a new analytical perspective for standard innovation research. Consistent with existing research, the mediating roles of OU and KRO have been confirmed [92,93]. However, most of the existing research on OU and KRO focuses on general product innovation and service innovation scenarios. This study introduces OU and KRO into the TSI research context, thereby expanding their application scope. Moreover, existing research often separately studies the mediating role of OU or KRO [31,94], rarely analyzing the progressive effect between them. This study proposes the “DO–OU–KRO–TSI” progressive transmission logic, filling the gap in existing research regarding the insufficient explanation of the intermediate process of digital strategy implementation. By establishing this comprehensive theoretical framework, this study deepens the systematic understanding of how DO affects TSI.

Finally, this study explores the inhibitory situational effect of KI during the transformation from OU to KRO. In existing research on the intersection of digitization and standardization, the role of knowledge barriers within organizations has been insufficiently examined [95]. Given the high level of knowledge complexity inherent in TSI, effective KRO places stringent demands on an enterprise’s internal context. In the process of transitioning from OU to KRO, enterprises are prone to constraints imposed by deeply entrenched existing knowledge systems [96]. Therefore, this study examines the moderating role of KI in the relationship between OU and KRO. It reveals the organizational barriers encountered during the transition from OU to KRO and enriches the understanding of KI’s boundary role in research on DO and TSI.

5.2. Managerial Implications

This study offers several insights for managers of traditional enterprises seeking to leverage DO to drive TSI. First, enterprises should prioritize top-level DO construction to lay a strategic foundation for TSI. Managers should elevate digitalization to a core strategic level to enhance adaptation to technological and market changes. Specifically, they can set up dedicated digital strategy committees to align digital investment with technology standardization objectives. Managers should conduct a digital maturity assessment to identify gaps in their standardization capabilities before implementing digital transforma-

tion initiatives. Enterprises can deploy digital resource discovery platforms in advance to prepare the resources needed for standard development.

Second, enterprises should systematically advance OU to break cognitive and routine path dependence for TSI. While digital technologies can boost efficiency, they may also foster technological dependency and diminish creativity, making proactive unlearning a prerequisite for standard innovation. Specifically, enterprises should carry out targeted reviews of outdated standard-setting processes and obsolete technology standard cognition, establishing formal retirement mechanisms for outdated standards and routines. Managers can regularly conduct training to update employee cognition, creating space for introducing new digital technologies and standardized knowledge required for TSI. Especially for resource-constrained enterprises, managers may prioritize low-cost OU activities to lay a foundation for cognitive transformation. They can gradually invest in digital tools and knowledge management platforms based on their own resource endowments, thereby preventing losses from blind investment and improving the return rate of digital transformation.

Third, enterprises should promote KRO while dynamically managing KI to secure TSI outcomes. On the resource construction side, enterprises should invest in knowledge management platforms that explicitly support the recombination and reconfiguration of standardized knowledge. Managers can build digital knowledge repositories to categorize, label and renew standardized knowledge generated by employees; they can also launch regular internal knowledge review workshops to stimulate internal knowledge creation activities. On the boundary governance side, given the negative moderating effect of KI, enterprises should dynamically monitor internal KI levels. Managers can arrange cross-departmental digital exchange seminars and set up external technical expert advisory groups to introduce cutting-edge standardized knowledge. Furthermore, routines such as closed internal assessment systems and exclusive reward frameworks tend to consolidate KI, while open standard innovation contests and job rotation schemes help mitigate it. Managers should implement knowledge rotation programs to reduce dependency on any single knowledge source or expert.

5.3. Limitations and Future Research Directions

This study has four main limitations. First, the cross-sectional data used in this study cannot fully explain the long-term dynamic effects of the serial mediation chain. A longitudinal tracking design would allow for more rigorous testing of the causal direction between DO and TSI. Future research could adopt longitudinal research designs to expand the generalizability of the findings. Second, although data from Chinese enterprises provide a suitable sample for validating our hypotheses, China's unique developmental stage and cultural context differ from those of other nations. These findings require further testing through cross-contextual empirical studies. Future research could conduct comparative analyses to clarify the impact of cross-cultural differences. Third, the sample data were not collected by industry segment, making it impossible to further analyze heterogeneity across industry segments. This limitation restricts the general applicability of the empirical results. Future research could conduct a secondary survey targeting specific industries to explore differences across industries within the research framework. Finally, the serial mediation effect observed in the research findings is relatively low, and the other potential conditional constraints remain unclear. Current research on DO and TSI is relatively fragmented. Future research could adopt the Systematic Search Flow review method [97] to synthesize the scattered empirical findings in this field, explore all potential boundary effects, and construct a more comprehensive theoretical framework.

6. Conclusions

Based on strategic management theory and resource orchestration theory, this study constructs a theoretical framework integrating DO, OU, KRO, TSI, and KI. Using PLS-SEM to examine data from 480 Chinese enterprises, it explores how and under what conditions DO promotes TSI. The empirical results indicate the following: First, DO positively influences TSI. Second, OU and KRO play a serial mediating role in the relationship between DO and TSI, forming a progressive transmission pathway of “strategic guidance–cognitive transformation–resource orchestration–innovation output”. Third, KI negatively moderates the transition from OU to KRO and serves as a key constraining variable in the serial mediation transmission process. The above findings reveal the underlying mechanisms of the transformation from DO to TSI from both strategic and resource perspectives. This study addresses the lack of attention in existing digitization and standardization research to serial mediation transmission mechanisms and boundary conditions.

Furthermore, we encourage subsequent scholars to build upon this research framework. Future studies could expand the scope of our analysis by incorporating cross-national comparative samples, dissecting industry heterogeneity, or adopting longitudinal research designs to capture dynamic causal relationships among variables. In management practice, this study provides actionable decision-making guidance for enterprises in designing digital strategies, optimizing knowledge management mechanisms, and advancing innovation in technology standards. Overall, this study constructs a comprehensive model that not only enriches theoretical system research at the intersecting fields of digitalization and standardization, but also provides systematic practical guidance for building standard competitiveness.

Author Contributions: Conceptualization, H.J., C.C. and Y.Y.; methodology, H.J., C.C. and Y.Y.; software, C.C. and Y.Y.; validation, H.J. and C.C.; formal analysis, H.J. and C.C.; investigation, H.J. and C.C.; resources, H.J.; data curation, H.J. and C.C.; writing—original draft preparation, H.J., C.C. and Y.Y.; writing—review and editing, H.J., C.C. and Y.Y.; visualization, H.J.; supervision, H.J. and C.C.; project administration, H.J. and C.C.; funding acquisition, H.J. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to acknowledge the grants from the National Natural Science Foundation of China (No.72372051); the Key Program of the National Natural Science Foundation of China (No. 72534003).

Institutional Review Board Statement: Ethical review and approval were waived for this study because it adopted anonymous questionnaire survey without collecting identifiable personal information. This study will not cause harm to participants and do not involve sensitive personal information or commercial interests. According to Article 32 of the “Measures for the Ethical Review of Life Science and Medical Research Involving Humans” (2023), jointly issued by the National Health Commission, the Ministry of Education, the Ministry of Science and Technology, and the National Administration of Traditional Chinese Medicine, “The following types of life science and medical research involving humans, which use information data or biological samples, may be exempt from ethical review if they cause no harm to humans and do not involve sensitive personal information or commercial interests.” https://www.gov.cn/zhengce/zhengceku/2023-02/28/content_5743658.htm (accessed on 10 June 2026).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available from the authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Vial, G. Understanding digital transformation: A review and a research agenda. *J. Strateg. Inf. Syst.* **2019**, *28*, 118–144. [\[CrossRef\]](#)
- Meier, A.; Eller, R.; Peters, M. Creating competitiveness in incumbent small- and medium-sized enterprises: A revised perspective on digital transformation. *J. Bus. Res.* **2025**, *186*, 115028. [\[CrossRef\]](#)
- Warner, K.S.R.; Wäger, M. Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Plan.* **2019**, *52*, 326–349. [\[CrossRef\]](#)
- Scott, S.; Orlikowski, W. The digital undertow: How the corollary effects of digital transformation affect industry standards. *Inf. Syst. Res.* **2021**, *33*, 311–336. [\[CrossRef\]](#)
- Blind, K.; Kenney, M.; Leiponen, A.; Simcoe, T. Standards and innovation: A review and introduction to the special issue. *Res. Policy* **2023**, *52*, 104830. [\[CrossRef\]](#)
- Foster, C.; Heeks, R. Innovation and scaling of ICT for the bottom-of-the-pyramid. *J. Inf. Technol.* **2013**, *28*, 296–315. [\[CrossRef\]](#)
- Kim, D.H.; Lee, H.; Kwak, J. Standards as a driving force that influences emerging technological trajectories in the converging world of the Internet and things: An investigation of the M2M/IoT patent network. *Res. Policy* **2017**, *46*, 1234–1254. [\[CrossRef\]](#)
- Farrell, J.; Simcoe, T. Four paths to compatibility. In *The Oxford Handbook of the Digital Economy*; Peitz, M., Waldfoegel, J., Eds.; Oxford University Press: New York, NY, USA, 2012; pp. 34–58. [\[CrossRef\]](#)
- Hodapp, D.; Hanelt, A. Interoperability in the era of digital innovation: An information systems research agenda. *J. Inf. Technol.* **2022**, *37*, 407–427. [\[CrossRef\]](#)
- Teece, D.J. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Policy* **2018**, *47*, 1367–1387. [\[CrossRef\]](#)
- Khin, S.; Ho, T.C. Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *Int. J. Innov. Sci.* **2019**, *11*, 177–195. [\[CrossRef\]](#)
- Ardito, L.; Raby, S.; Albino, V.; Bertoldi, B. The duality of digital and environmental orientations in the context of SMEs: Implications for innovation performance. *J. Bus. Res.* **2021**, *123*, 44–56. [\[CrossRef\]](#)
- Zhang, X.E.; Yang, L.; Wang, W.; Yu, Y.B. The impact of digital orientation on digital innovation performance of Chinese SRDI small and medium-sized enterprises: A knowledge creation perspective. *J. Knowl. Manag.* **2026**, *Epub ahead of printing*. [\[CrossRef\]](#)
- Li, X.; Zhang, X. Manufacturing firms: Digital orientation and sustainable performance. *Manag. Decis.* **2026**, *64*, 2034–2058. [\[CrossRef\]](#)
- Techatassanasoontorn, A.A.; Suo, S.G. Influences on standards adoption in de facto standardization. *Inf. Technol. Manag.* **2011**, *12*, 357–385. [\[CrossRef\]](#)
- Grégoire-Zawilski, M.; Popp, D. Do technology standards induce innovation in environmental technologies when coordination is important? *Res. Policy* **2024**, *53*, 104888. [\[CrossRef\]](#)
- Foucart, R.; Li, Q.C. The role of technology standards in product innovation: Theory and evidence from UK manufacturing firms. *Res. Policy* **2021**, *50*, 104157. [\[CrossRef\]](#)
- Akhtar, S.; Tian, H.Y.; Hassan, S.G.; Iqbal, S. Assessing the impact of environmental orientation on green innovation performance in the era of digital transformation in tourism SMEs. *Technol. Anal. Strateg. Manag.* **2026**, *Epub ahead of printing*. [\[CrossRef\]](#)
- Mikalef, P.; van de Wetering, R.; Krogstie, J. Building dynamic capabilities by leveraging big data analytics: The role of organizational inertia. *Inf. Manag.* **2021**, *58*, 103412. [\[CrossRef\]](#)
- Wang, X.Y.; Liu, Z.Y.; Li, J.M.; Lei, X.F. How organizational unlearning leverages digital process innovation to improve performance: The moderating effects of smart technologies and environmental turbulence. *Technol. Soc.* **2023**, *75*, 102395. [\[CrossRef\]](#)
- Cheng, Q.; Liu, Y.; Peng, C.; He, X.S.; Qu, Z.Q.; Dong, Q.Y. Knowledge digitization: Characteristics, knowledge advantage and innovation performance. *J. Bus. Res.* **2023**, *163*, 113915. [\[CrossRef\]](#)
- Sirmon, D.G.; Hitt, M.A.; Ireland, R.D.; Gilbert, B.A. Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *J. Manag.* **2011**, *37*, 1390–1412. [\[CrossRef\]](#)
- Gilbert, C.G. Unbundling the structure of inertia: Resource versus routine rigidity. *Acad. Manag. J.* **2005**, *48*, 741–763. [\[CrossRef\]](#)
- Bai, J.K.; Zha, Y.F.; Zhang, H.X.; Wang, C.Q.; Mavroudi, E. Relating digital platform synergy and SME agility: The roles of organizational inertia and modularity. *Inf. Manag.* **2026**, *63*, 104279. [\[CrossRef\]](#)
- Maccioni, S.; Ghiringhelli, C.; Datteri, E. Navigating the unlearning landscape: An organizational unlearning taxonomy and an outcome-centric model. *Learn. Organ.* **2024**, *31*, 960–984. [\[CrossRef\]](#)
- Surdu, I.; Narula, R. Organizational learning, unlearning and re-internationalization timing: Differences between emerging-versus developed-market MNEs. *J. Int. Manag.* **2021**, *27*, 100784. [\[CrossRef\]](#)
- Li, L.X.; Ye, F.; Zhan, Y.Z.; Kumar, A.; Schiavone, F.; Li, Y.N. Unraveling the performance puzzle of digitalization: Evidence from manufacturing firms. *J. Bus. Res.* **2022**, *149*, 54–64. [\[CrossRef\]](#)
- Liao, S.H. Problem solving and knowledge inertia. *Expert Syst. Appl.* **2002**, *22*, 21–31. [\[CrossRef\]](#)
- Wang, X.Y.; Liu, Z.Y.; Lei, X.F. How digital orientation promotes digital process innovation from the perspectives of knowledge and capability: Evidence from China. *J. Knowl. Manag.* **2025**, *29*, 259–280. [\[CrossRef\]](#)

30. Lyu, C.; Yang, J.J.; Zhang, F.; Teo, T.S.H.; Gue, W.Y. Antecedents and consequence of organizational unlearning: Evidence from China. *Ind. Mark. Manag.* **2020**, *84*, 261–270. [\[CrossRef\]](#)
31. Tang, H.J.; Xie, Y.; Liu, Y.Q.; Boadu, F. Distributed innovation, knowledge re-orchestration, and digital product innovation performance: The moderated mediation roles of intellectual property protection and knowledge exchange activities. *J. Knowl. Manag.* **2023**, *27*, 2686–2707. [\[CrossRef\]](#)
32. Wen, J.Y.; Li, J.; Zhou, Q.; Zeng, D.M.; Harms, R. How firms support formal standardization: The role of alliance portfolio and internal technological diversity. *Technol. Forecast. Soc. Change* **2023**, *196*, 122854. [\[CrossRef\]](#)
33. Gatignon, H.; Xuereb, J.M. Strategic orientation of the firm and new product performance. *J. Mark. Res.* **1997**, *34*, 77–90. [\[CrossRef\]](#)
34. Dao, V.T.; Zmud, B. The influence of technology-related, market-related, and standards-related strategic signaling during a standards war. *IEEE Trans. Eng. Manag.* **2015**, *62*, 300–310. [\[CrossRef\]](#)
35. Bendig, D.; Schulz, C.; Theis, L.; Raff, S. Digital orientation and environmental performance in times of technological change. *Technol. Forecast. Soc. Change* **2023**, *188*, 122272. [\[CrossRef\]](#)
36. Besson, P.; Rowel, F. Strategizing information systems-enabled organizational transformation: A transdisciplinary review and new directions. *J. Strateg. Inf. Syst.* **2012**, *21*, 103–124. [\[CrossRef\]](#)
37. Moradi, E.; Jafari, S.M.; Doorbash, Z.M.; Mirzaei, A. Impact of organizational inertia on business model innovation, open innovation and corporate performance. *Asia Pac. Manag. Rev.* **2021**, *26*, 171–179. [\[CrossRef\]](#)
38. Tjahjadi, B.; Soewarno, N.; Sutarsa, A.A.P.; Jermias, J. Effect of intellectual capital on organizational performance in the Indonesian SOEs and subsidiaries: Roles of open innovation and organizational inertia. *J. Intellect. Cap.* **2024**, *25*, 423–447. [\[CrossRef\]](#)
39. Sirmon, D.G.; Hitt, M.A.; Ireland, R.D. Managing firm resources in dynamic environments to create value: Looking inside the black box. *Acad. Manag. Rev.* **2007**, *32*, 273–292. [\[CrossRef\]](#)
40. Nassani, A.A.; Aldakhil, A.M. Tackling organizational innovativeness through strategic orientation: Strategic alignment and moderating role of strategic flexibility. *Eur. J. Innov. Manag.* **2023**, *26*, 847–861. [\[CrossRef\]](#)
41. Xu, L.D.; He, W.; Li, S.C. Internet of things in industries: A survey. *IEEE Trans. Ind. Inform.* **2014**, *10*, 2233–2243. [\[CrossRef\]](#)
42. Jiang, H.; Motohashi, K.; Liu, W.T.; Zhang, X. Knowledge-oriented leadership and technology standard innovation: A temporary-team perspective. *J. Knowl. Manag.* **2022**, *26*, 2061–2083. [\[CrossRef\]](#)
43. Bergeaud, A.; Schmidt, J.; Zago, R. Patents that match your standards: Firm-level evidence on competition, innovation and growth. *J. Financ. Econ.* **2026**, *180*, 104281. [\[CrossRef\]](#)
44. Jeon, K.; Lee, G.; Kang, S.; Roh, H.; Jung, J.; Lee, K.; Baldwin, M. A relational framework for smart information delivery manual (IDM) specifications. *Adv. Eng. Inform.* **2021**, *49*, 101319. [\[CrossRef\]](#)
45. Gao, Q.; Cheng, C.M.; Sun, G.L. Big data application, factor allocation, and green innovation in Chinese manufacturing enterprises. *Technol. Forecast. Soc. Change* **2023**, *192*, 122567. [\[CrossRef\]](#)
46. Kindermann, B.; Beutel, S.; de Lomana, G.G.; Strese, S.; Bendig, D.; Brettel, M. Digital orientation: Conceptualization and operationalization of a new strategic orientation. *Eur. Manag. J.* **2021**, *39*, 645–657. [\[CrossRef\]](#)
47. Ranjan, P. Unraveling the mystery of the link between digital orientation and innovation performance: The interplay of digital business capability and environmental dynamism. *Technovation* **2024**, *131*, 102966. [\[CrossRef\]](#)
48. Prahalad, C.K.; Bettis, R.A. The dominant logic—A new linkage between diversity and performance. *Strateg. Manag. J.* **1986**, *7*, 485–501. [\[CrossRef\]](#)
49. Fiol, C.M.; O'Connor, E.J. Unlearning established organizational routines—Part II. *Learn. Organ.* **2017**, *24*, 82–92. [\[CrossRef\]](#)
50. Dayan, M.; Benedetto, C.A.D.; Dayan, B.; Rumaithi, E.A.; Zahmi, R.A. How much internationalization is innovation-worthy for SMEs? Roles of the degree of internationalization and organizational unlearning on the joint innovation capabilities-exploratory innovation relationship. *J. Innov. Knowl.* **2024**, *9*, 100614. [\[CrossRef\]](#)
51. Becker, K. Unlearning as a driver of sustainable change and innovation: Three Australian case studies. *Int. J. Technol. Manag.* **2008**, *42*, 89–106. [\[CrossRef\]](#)
52. Morais-Storz, M.; Nguyen, N. The role of unlearning in metamorphosis and strategic resilience. *Learn. Organ.* **2017**, *24*, 93–106. [\[CrossRef\]](#)
53. Grant, R.M. Prospering in dynamically competitive environments: Organizational capability as knowledge integration. *Organ. Sci.* **1996**, *7*, 375–387. [\[CrossRef\]](#)
54. Di Vaio, A.; Palladino, R.; Pezzi, A.; Kalisz, D.E. The role of digital innovation in knowledge management systems: A systematic literature review. *J. Bus. Res.* **2021**, *123*, 220–231. [\[CrossRef\]](#)
55. Plekhanov, D.; Franke, H.; Netland, T.H. Digital transformation: A review and research agenda. *Eur. Manag. J.* **2023**, *41*, 821–844. [\[CrossRef\]](#)
56. Bereznoy, A.; Meissner, D.; Scuotto, V. The intertwining of knowledge sharing and creation in the digital platform based ecosystem. A conceptual study on the lens of the open innovation approach. *J. Knowl. Manag.* **2021**, *25*, 2022–2042. [\[CrossRef\]](#)

57. Ahmed, A.; Bhatti, S.H.; Gölgeci, I.; Arslan, A. Digital platform capability and organizational agility of emerging market manufacturing SMEs: The mediating role of intellectual capital and the moderating role of environmental dynamism. *Technol. Forecast. Soc. Change* **2022**, *177*, 121513. [\[CrossRef\]](#)
58. Baron, J.; Pohlmann, T. Mapping standards to patents using declarations of standard-essential patents. *J. Econ. Manag. Strategy* **2018**, *27*, 504–534. [\[CrossRef\]](#)
59. Rysman, M.; Simcoe, T. Patents and the performance of voluntary standard-setting organizations. *Manag. Sci.* **2008**, *54*, 1920–1934. [\[CrossRef\]](#)
60. Yoo, Y.; Lyytinen, K.; Yang, H.D. The role of standards in innovation and diffusion of broadband mobile services: The case of South Korea. *J. Strateg. Inf. Syst.* **2005**, *14*, 323–353. [\[CrossRef\]](#)
61. Tian, C.; Zhang, J.Y.; Liu, D.Y. Knowledge sources, novelty, and generality: Do standard-essential patents differ from nonstandard-essential ones? *IEEE Trans. Eng. Manag.* **2023**, *71*, 6796–6811. [\[CrossRef\]](#)
62. Zhao, Y.X.; Lu, Y.Q.; Wang, X.Y. Organizational unlearning and organizational relearning: A dynamic process of knowledge management. *J. Knowl. Manag.* **2013**, *17*, 902–912. [\[CrossRef\]](#)
63. Becker, K. Facilitating unlearning during implementation of new technology. *J. Organ. Chang. Manag.* **2010**, *23*, 251–268. [\[CrossRef\]](#)
64. Tsang, E.W.K. Transferring knowledge to acquisition joint ventures: An organizational unlearning perspective. *Manag. Learn.* **2008**, *39*, 5–20. [\[CrossRef\]](#)
65. Zhang, F.; Lyu, C.C.; Zhu, L. Organizational unlearning, knowledge generation strategies and radical innovation performance: Evidence from a transitional economy. *Eur. J. Mark.* **2022**, *56*, 133–158. [\[CrossRef\]](#)
66. Akgün, A.E.; Byrne, J.C.; Lynn, G.S.; Keskin, H. New product development in turbulent environments: Impact of improvisation and unlearning on new product performance. *J. Eng. Technol. Manag.* **2007**, *24*, 203–230. [\[CrossRef\]](#)
67. Huang, H.C.; Lai, M.C.; Lin, L.H.; Chen, C.T. Overcoming organizational inertia to strengthen business model innovation: An open innovation perspective. *J. Organ. Change Manag.* **2013**, *26*, 977–1002. [\[CrossRef\]](#)
68. Ghezzi, A.; Cavallo, A. Agile business model innovation in digital entrepreneurship: Lean startup approaches. *J. Bus. Res.* **2020**, *110*, 519–537. [\[CrossRef\]](#)
69. Jalowski, M.; Oks, S.J.; Möslin, K.M. Fostering knowledge sharing: Design principles for persuasive digital technologies in open innovation projects. *Creat. Innov. Manag.* **2023**, *32*, 233–248. [\[CrossRef\]](#)
70. Martignoni, D.; Keil, T. It did not work? Unlearn and try again—Unlearning success and failure beliefs in changing environments. *Strateg. Manag. J.* **2021**, *42*, 1057–1082. [\[CrossRef\]](#)
71. Xie, Z.J.; Hall, J.; McCarthy, I.P.; Skitmore, M.; Shen, L.Y. Standardization efforts: The relationship between knowledge dimensions, search processes and innovation outcomes. *Technovation* **2016**, *48–49*, 69–78. [\[CrossRef\]](#)
72. Yu, B.; Hao, S.B.; Wang, Y. Organizational search and business model innovation: The moderating role of knowledge inertia. *J. Knowl. Manag.* **2020**, *24*, 1705–1718. [\[CrossRef\]](#)
73. Fu, X.R.; Luan, R.; Wu, H.H.; Zhu, W.T.; Pang, J. Ambidextrous balance and channel innovation ability in Chinese business circles: The mediating effect of knowledge inertia and guanxi inertia. *Ind. Mark. Manag.* **2021**, *93*, 63–75. [\[CrossRef\]](#)
74. Quinton, S.; Canhoto, A.; Molinillo, S.; Pera, R.; Budhathoki, T. Conceptualising a digital orientation: Antecedents of supporting SME performance in the digital economy. *J. Strateg. Mark.* **2018**, *26*, 427–439. [\[CrossRef\]](#)
75. Arias-Pérez, J.; Vélez-Jaramillo, J. Ignoring the three-way interaction of digital orientation, Not-invented-here syndrome and employee's artificial intelligence awareness in digital innovation performance: A recipe for failure. *Technol. Forecast. Soc. Change* **2022**, *174*, 121305. [\[CrossRef\]](#)
76. Adams, P.; Freitas, I.M.B.; Fontana, R. Strategic orientation, innovation performance and the moderating influence of marketing management. *J. Bus. Res.* **2019**, *97*, 129–140. [\[CrossRef\]](#)
77. Faul, F.; Erdfelder, E.; Lang, A.G.; Buchner, A. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* **2007**, *39*, 175–191. [\[CrossRef\]](#) [\[PubMed\]](#)
78. Fuller, C.M.; Simmering, M.J.; Atinc, G.; Atinc, Y.; Babin, B.J. Common methods variance detection in business research. *J. Bus. Res.* **2016**, *69*, 3192–3198. [\[CrossRef\]](#)
79. Kindermann, B.; Schmidt, C.V.H.; Fengel, F.; Strese, S. Expanding the boundaries of digital orientation research: Scale development and validation. *J. Bus. Res.* **2024**, *185*, 114895. [\[CrossRef\]](#)
80. Teece, D.J. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strateg. Manag. J.* **2007**, *28*, 1319–1350. [\[CrossRef\]](#)
81. Dávila, G.A.; Andreeva, T.; Saetre, A.S. Using social integration mechanisms to boost absorptive capacity: Walking a tightrope. *Eur. Manag. Rev.* **2025**, *22*, 619–639. [\[CrossRef\]](#)
82. Ahmadova, G.; Delgado-Márquez, B.L.; Pedauga, L.E.; Leyva-De la Hiz, D. Too good to be true: The inverted U-shaped relationship between home-country digitalization and environmental performance. *Ecol. Econ.* **2022**, *196*, 107393. [\[CrossRef\]](#)
83. Li, R.J.; Fu, L.H.; Liu, Z.Y. The paradoxical effect of digital transformation on innovation performance: Does risk-taking matter? *IEEE Trans. Eng. Manag.* **2024**, *71*, 3308–3324. [\[CrossRef\]](#)

84. Xie, X.W.; Zhang, L.S.; Bai, Y.T.; Zhu, H.Y. Firm' digital orientation and ESG performance: An inverted U-shaped analysis. *Manag. Decis.* **2025**. *Epub ahead of printing*. [[CrossRef](#)]
85. Zhang, F.; Ye, D.P.; Pang, K.X.; Zhu, L.; Zhu, M.J. Enhancing digital transformation competency in traditional manufacturing firms: The role of organizational unlearning and strategic flexibility. *Ind. Manag. Data Syst.* **2026**. *Epub ahead of printing*. [[CrossRef](#)]
86. Shu, C.L.; Wang, Q.; Gao, S.X.; Liu, C.J. Firm patenting, innovations, and government institutional support as a double-edged sword. *J. Prod. Innov. Manag.* **2015**, *32*, 290–305. [[CrossRef](#)]
87. Zhang, F.; Wang, J.J.; Kang, M.B.; Zhu, L. Leveraging organizational unlearning for digital business model innovation: The roles of dynamic capability and institutional forces. *Int. J. Oper. Prod. Manag.* **2026**, *46*, 1223–1247. [[CrossRef](#)]
88. Wen, J.Y.; Tan, D.H.; Wang, H.L.; Gao, Y.X. How do alliance networks affect firms' capability of influencing technological standardization? Configuration analysis based on the toe framework. *Sustainability* **2025**, *17*, 9499. [[CrossRef](#)]
89. Xie, X.; Wu, S.K.; Subhani, G.; Sakina. Analyzing how digital orientation contributes to organizational innovation and environmental, social and governance performance through digital inclusion and capabilities. *Int. Entrep. Manag. J.* **2025**, *21*, 83. [[CrossRef](#)]
90. Costabile, C.; Iden, J.; Bygstad, B. Building digital platform ecosystems through standardization: An institutional work approach. *Electron. Mark.* **2022**, *32*, 1877–1889. [[CrossRef](#)] [[PubMed](#)]
91. Tumpa, R.J.; Naeni, L.M.; Afzal, F.; Ghanbaripour, A.N. Leveraging digital technology to improve environmental, social, and governance performance of infrastructure projects. *Manag. Decis.* **2025**, *63*, 455–496. [[CrossRef](#)]
92. Rahardjo, A.A.; Lim, W.L.; Tan, G.W.H. How does entrepreneurial orientation influence organisational ambidexterity? Moderating effect of organisational unlearning. *Int. J. Innov. Learn.* **2024**, *36*, 140875. [[CrossRef](#)]
93. Shang, T.T.; Dong, G.M.; Tian, M. Digital transformation and disruptive green innovation: The role of organisational unlearning and organisational flexibility. *Technol. Anal. Strateg. Manag.* **2025**. *Epub ahead of printing*. [[CrossRef](#)]
94. Yeniaras, V.; Di Benedetto, A.; Kaya, I.; Dayan, M. Relational governance, organizational unlearning and learning: Implications for performance. *J. Bus. Ind. Mark.* **2021**, *36*, 469–492. [[CrossRef](#)]
95. Gao, Q.Y.; Wang, Q.; Wu, C.S. Construction of enterprise digital service and operation platform based on internet of things technology. *J. Innov. Knowl.* **2023**, *8*, 100433. [[CrossRef](#)]
96. Fan, Q.; Liu, L.J.; Wan, W.H. Exploring the impact of digital enabling data systems on the innovation performance of digital service firms: The roles of knowledge reconfiguration and knowledge inertia. *Serv. Bus.* **2026**, *20*, 15. [[CrossRef](#)]
97. Ferenhof, H.A.; Fernandes, R.F. Demystifying literature review in the AI Era: Updating the SSF method with Generative Artificial Intelligence support. *Biblios* **2025**, *88*, e003. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.